Journal of Environmental Management 241 (2019) 353–362

Contents lists available at ScienceDirect

Journal of Environmental Management

journal homepage: www.elsevier.com/locate/jenvman

Research article

Decentralized allocation of emission permits by Nash data envelopment analysis in the coal-fired power market

Chia-Yen Lee

Institute of Manufacturing Information and Systems, National Cheng Kung University, Tainan City, 701, Taiwan

ARTICLE INFO

Keywords:
Data envelopment analysis
Emission permit
Nash equilibrium
Decentralized allocation
Coal-fired power plant

ABSTRACT

Allocation of emission permits (AEP) provides valuable guidelines to support environmental regulatory policies for pollutant emission, in particular, CO_2 as the key contributors to climate change. Most of previous studies in literature developed the centralized AEP model and focused on the coal-fired power market, one of the main sources of air pollution. However, the power market is usually imperfectly competitive and some of them are gradually deregulated, this justifies the motivation of developing a decentralized AEP model. This study proposes a decentralized AEP model which suggests Nash equilibrium as an allocatively efficient benchmark in an imperfectly competitive market with endogenous price. The proposed model is formulated by data envelopment analysis (DEA) and transformed into the mixed complementarity problem (MiCP) for identifying the Nash equilibrium. A study of coal-fired power plants operating in China in 2013 is conducted and the results show that the decentralized model complements the centralized model; in particular, with considering the price and market structure, the proposed decentralized model described in this study investigates the potential for efficiency improvement after AEP among the coal-fired plants.

1. Introduction

Due to the severe challenges from climate changes, allocation of emission permits (AEP) (also called carbon emission abatement, CEA) is one method of building mechanism to allocate the pollution abatement quantity (or allowance) to the specific areas or organizations for achieving the target of pollution reduction. In fact, two decades ago, Greenhouse Development Rights (GDRs) were developed to provide a framework for sharing the costs of rapid climate change among countries (Berk and den Elzen, 2001). The one of the most famous international agreement— the Kyoto Protocol in 1997, introduces a market mechanism asking the developed nations to reducing the greenhouse gas emissions by 5.2% below 1990 levels by 2012 in Annex 1 (King et al., 2011). Recently, in December of 2015 in Paris conference, 187 countries adopted a historic international agreement on addressing global climate change that their governments agreed to a target of peaking the global greenhouse gas emissions so as to keep the increase of global average temperature below 2 °C and to pursuing effort to limit it to 1.5 °C above preindustrial levels.

China continues to be one of the world's major CO_2 emitters. Since 2007, China has become the world's largest contributor to carbon emissions from fossil fuel burning and cement production, and responsible for approximate 25 percent of global carbon emissions; its manufacturing and power generation sectors accounted for 85 percent of China's total carbon emissions (Liu, 2015). In 2009, China claimed it would decrease its CO_2 emissions per unit of GDP (i.e., carbon intensity) by 40–45% by 2020 using 2005 as the reference year, and then set a target to reduce carbon intensity by 17% by 2015 compared to 2010. Since 2013, seven pilot provinces and provincial cities, Shenzhen, Shanghai, Beijing, Guangdong, Tianjin, Chongqing, and Hubei, successively launched their own emission trading schemes (ETS) (Lee and Zhou, 2015; Lee and Wang, 2019). These regional pilot carbon markets are regarded as indispensable experiments prior to establishing a national ETS. In 2015, before the Paris conference, China submitted its INDC which includes three major elements regarding emissions: (i) to peak CO_2 emissions no later than 2030, (ii) to increase the share of non-fossil fuels in the total primary energy supply to 20% by 2030, and (iii) to reduce the carbon intensity of GDP by 60–65% compared to 2005 levels by 2030 (den Elzen et al., 2016).

From the perspective of policy-makers, a deeper understanding of AEP will help China's regional government formulate appropriate carbon abatement policies, such as carbon pricing through emission allowance allocations. To investigate China's emissions, this study focuses on coal-fired power plants and uses the North and the Northeast regions as a case for suggesting AEP allocation of CO_2 due to a high concentration of CO_2 emissions in the two regions in 2015 (Deng et al.,

E-mail address: cylee@mail.ncku.edu.tw.

https://doi.org/10.1016/j.jenvman.2019.03.114
Received 26 March 2018; Received in revised form 26 February 2019; Accepted 25 March 2019
Available online 23 April 2019

2015).

Data envelopment analysis (DEA) is a nonparametric method which can consider the desirable outputs and undesirable outputs simultaneously to estimate the production function and technical efficiency without a specified functional form (Dakpo et al., 2016). Besides to the ex-post efficiency analysis, DEA based on linear programming technique can also be applied to ex-ante analysis for planning resource allocation, in particular, AEP in this study. Gomes and Lins (2008) developed zero sum gains DEA (ZSG-DEA) models and suggested uniform DEA frontier to reallocate the CO2 emissions among the 64 signatory countries of the Kyoto protocol. They assumed the cooperation among decision making units (DMUs) and each DMU adjusted CO2 emissions regarded as input factor to ensure all the DMUs become efficient after reallocation. However, the perfect cooperation assumption may not be applicable to the real practice, and thus the result presented a fair but too ideal allocation of the CO2 emission. They also treated the undesirable outputs as inputs and did not consider the weak disposability between good outputs and bad outputs. Lozano et al. (2009) implemented the centralized AEP model by using three objectives separately: maximizing aggregated desirable production, minimizing undesirable total emissions, and minimizing the consumption of input resources. Their model introduces nonradial and unit-invariant performance metrics as objective functions, and sets the priorities in terms of the lexicographic order. The approach was applied to 41 plants from the Swedish pulp and paper industry. Their approach benefits the technical and environmental efficiency; however, it cannot be justified from the allocative efficiency or economic efficiency without price information. Sun et al. (2014) proposed the individual AEP where a dominating firm enjoys the right of AEP and all the other firms just follow while the central AEP where a governing body is established to coordinate the AEP among member firms in the group. A case study of paper mills in the Huai River region in China has been conducted to build the relationship between the DEA efficiency and AEP; however, they also treated the undesirable outputs as inputs. Feng et al. (2015) proposed a two-step procedure to suggest the allocation of the carbon emissions abatement which gave a balance between the overall and individual interests. In the first step, they developed a centralized DEA model with constant-return-to-scale (CRS) and variable-return-to-scale (VRS) assumptions to allocate emission permits to participating countries, aiming at maximizing the total potential gross domestic product (GDP). To alleviate the conflict of the overall and individual interests, in the second step, they provided two compensate schemes according to their AEP contributions, an average price of CO_2 emissions, and bankruptcy model used to allocate a whole estate to different claimants fairly. An application to the 21 countries in Organization for Economic Co-operation and Development (OECD) is presented. However, the average price of CO_2 calculated in this study was regarded as a dummy price significantly affected by the pre-determined distributive factor. Ji et al. (2017a) divided the timing of AEP process into one observation pre-stage and one two-stage regulatory scheme which is evident in many of China's regional environmental management plans. They provided the stage-by-stage state variations of the explicit characterizations and then apply the derived final systemic state variables to create an AEP model by DEA. An empirical study of China's coal-fired power plants in 2012 is used to demonstrate the AEP process. They claimed that the proposed scheme can release the effect of a certain cap-and-trade emission regulation policy, although no individual is given an incentive to trade owned permits. Ji et al. (2017b) proposed a robust multicriteria centralized model for AEP in large data sets. They generalized conventional concepts of the efficient frontier and feasible production set for the cases involving large data sets. They also considered the emission standard as a control variable, and finds its optimal value together with each DMU's optimal emission permits. The model is applied to allocate SO_2 emission permits in the 202 Chinese prefecture-level cities. However, they also treated the undesirable outputs as inputs and did not consider the weak disposability.

Due to some drawbacks mentioned in literature, the current study formulates the weak disposability between desirable and undesirable outputs, distinguishes the fixed inputs from the variable inputs in the production technology, considers an imperfectly competitive energy market with an endogenous price, and finally develops a decentralized AEP models toward the Nash equilibrium with respect to individual profit maximization. The current study contributes to the following three points in literature.

First, recall that the DEA estimator assumes that the desirable outputs are freely disposable; this property, however, cannot be directly applied to undesirable outputs. Intuitively, we can reduce the level of the desirable output which will result in a proportionate reduction of the undesirable outputs. In other words, the free (or strong) disposability assumption ignores the possibility to decrease undesirable outputs by down-sizing the activity level, i.e., a proportional contraction of desirable outputs and undesirable outputs is feasible simultaneously. This property, termed “weak disposability,” was originally proposed by Shephard (1974). The current study introduces the Färe's convex technology with respect to CRS, VRS, and non-increasing returns-to-scale (NIRS) (Chung et al., 1997; Zhou et al., 2008).

Second, typical studies of AEP studies implicitly assume a cooperative game or perfectly competitive market with an exogenous market price, and thus develop the centralized AEP models. In practice, however, the energy market is an imperfectly competitive market and the market price can be affected by the total supply generated by all firms in the market (Hobbs and Pang, 2007; Gabriel et al., 2013), i.e., the market price is endogenous. We consider a non-cooperative game characterized by the inverse demand function (i.e., price function) in an imperfectly competitive power market to develop the decentralized AEP with respect to the Nash equilibrium. We suggest the Nash equilibrium as an allocatively efficient benchmark under a competitive production behavior, and thus projecting the inefficient firm toward a Nash solution has important economic implications. For the literature of DEA game, see Banker (1980), Banker et al. (1989), Aparicio et al. (2008), Wu et al. (2009), Lozano (2013), and Lee (2018).

Third, in general, all production factors are adjustable in the long run. However, in the short run, the plant size, location, and capital stock for production are typically fixed, whereas the variable factors such as employment and material are adjustable (Marshall, 1920). Stigler (1939) argues that the quantitative variations of output can be described via the law of diminishing returns and marginal productivity theory when holding all but one the productive factors as constant and adjusting the quantity of the remaining factor. Johansen (1968) definition of physical capacity, which is the maximum amount that can be produced with existing plant and equipment (fixed inputs) given an unlimited availability of variable factors. Therefore, to address the electricity supply in the power system, it is necessary to distinguish the fixed factors (eg. nameplate capacity) and variable factors (eg. coal burned) for estimating the production function accurately.

The remainder of this paper is organized as follows. Section 2 introduces the weak disposability and Färe's technology for estimating the production possibility set and technical efficiency. Section 3 introduces the mathematical formulations of three centralized AEP models (i.e. egalitarianism model, Lozano model, and Feng model). Section 4 introduces the endogenous price with the inverse demand function and proposes two mixed complementarity problem (MiCP) models (i.e. Nash CRS model and Nash NIRS model) to identify the Nash equilibrium for decentralized AEP. Section 5 gives an empirical study of China's coal power industry to estimate the AEP and shows a comparison between the centralized models and decentralized models. Furthermore, we provide the efficiency analysis before AEP and after AEP to investigate how the AEP affect the power market and provide managerial insights. Section 6 concludes and suggests further research.

2. Weak disposability and Färe's technology

This section introduces the weak disposability and Färe's Technology (Chung et al., 1997). Consider a multiple-input and multiple-output production process. Let $\boldsymbol{x} \in \mathbb{R}_+^{|I|}$ denote a vector of input variables, $\boldsymbol{y} \in \mathbb{R}_+^{|J|}$ denote a vector of desirable output variables, and $\boldsymbol{b} \in \mathbb{R}_+^{|Q|}$ denote a vector of undesirable output variables for a production system. The production possibility set (PPS) T is defined as $T = \{(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{b}): \boldsymbol{x} \text{ can produce } (\boldsymbol{y}, \boldsymbol{b})\}$, i.e., $(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{b}) \in T$ and assume T is a convex set.

In the present study, we investigate the coal-fired power plants and consider electricity generation as a single desirable output, and CO_2 emission as a single undesirable output for AEP. Let index $i \in I$ represent the input and index $k \in K$ denote the DMU or firm index. Observations X_{ik} represent the ith input level, Y_k the single desirable output level, and B_k the single undesirable output level of firm k. Since desirable outputs and undesirable outputs are generated simultaneously, the PPS is developed based on three axioms (Lee et al., 2002; Färe et al., 2007; Lee, 2015; Wang et al., 2017). They are free disposability between inputs and desirable outputs, weak disposability between desirable outputs and undesirable outputs, and nulljointness of desirable outputs and undesirable outputs.

To formulate the weak disposability, we introduce Färe's CRS convex technology. Let λ_k be the decision variable representing the intensity weights of the convex combination between firms. Here, we separate the fixed inputs from the variable inputs. Estimate Färe's convex technology T^{CRS}.

$$\tilde{T}^{CRS} = \left\{ (\boldsymbol{x}, y, b) | \begin{array}{c} \sum_{k \in K} \lambda_k X_{ik} \le x_i, \forall\, i \in I; \\ \sum_{k \in K} \lambda_k Y_k \ge y; \\ \sum_{k \in K} \lambda_k B_k = b; \\ \lambda_k, x_i, y, b \ge 0, \forall\, k \in K,\ \ i \in I \end{array} \right\} \tag{1}$$

We also introduce Färe's VRS convex technology T^{VRS}. Note that this is the linearized version of Färe's VRS technology. See Zhou et al. (2008) for details.

$$\tilde{T}^{VRS} = \left\{ (\boldsymbol{x}, y, b) | \begin{array}{c} \sum_{k \in K} \lambda_k X_{ik} \le \xi x_i, \forall\, i \in I; \\ \sum_{k \in K} \lambda_k Y_k \ge y; \\ \sum_{k \in K} \lambda_k B_k = b; \\ \sum_{k \in K} \lambda_k = \xi; \\ \xi \le 1 \\ \lambda_k, x_i, y, b \ge 0, \forall\, k \in K,\ \ i \in I \end{array} \right\} \tag{2}$$

where ξ be the decision variable addressing the nonlinear formulation proposed by Färe and Grosskopf (2004) into a linear form (Zhou et al., 2008).

To measure the technical efficiency, we reduce the bad outputs for efficiency estimation due to focusing on the AEP. That is, given index $r \in K$ representing one specific firm and an alias of index k, estimate the efficiency of firm r in terms of the abatement potential in undesirable by using linear programming (3).

$$\begin{aligned} &\text{Min } \theta \\ &\text{s.t. } \sum_{k \in K} \lambda_k X_{ik} \le \xi X_{ir}, \forall\, i \in I \\ &\sum_{k \in K} \lambda_k Y_k \ge Y_r \\ &\sum_{k \in K} \lambda_k B_k = \theta B_r \\ &\sum_{k \in K} \lambda_k = \xi; \\ &\lambda_k \ge 0,\ \forall\, k \end{aligned} \tag{3}$$

where θ is the decision variable representing the efficiency measure. Thus, if $\theta = 1$, then firm r is efficient; otherwise it is inefficient if $\theta < 1$.

3. Centralized AEP model

This section introduces some typical AEP models. The first AEP model is based on egalitarianism (egalitarianism model hereafter). Egalitarianism is a trend of thought that favors equality for particular categories of, or for all, living entities. All the plants should get the same, or be treated as equals, in some respect. According to this principle, the initial allocation of the AEP should be calculated based on its initial proportion based on the population of each decision making unit (DMU) (i.e. plant) (Feng et al., 2015). This allocation means that the population of a county is an important criterion in the AEP allocation negotiations. Let P_k be the population size of plant k, and C be the "Cap" representing the target of the total amount of the carbon emission abatement in a specific period. The decision variable Δb_k is the adjusted AEP; that is, $\sum_{k \in K} \Delta b_k = C$. Thus, egalitarianism model suggests $\Delta b_k = C \times P_k / \sum_{k \in K} P_k$ for all $k \in K$.

3.1. Lozano model

Next, we introduce the second AEP model— a DEA formulation for the centralized AEP proposed by Lozano et al. (2009) (i.e., Lozano model hereafter). The Lozano model, based on Färe's weak disposability (Färe and Grosskopf, 2004), proposes the AEP using DEA formulation. The Lozano model suggests CRS assumption and a three-phase model with the priority of three objective functions. First phase maximizes the aggregated electricity generation, second phase minimizes the total emission of undesirable output, and third phase is to minimize the use of variable inputs of the plants. For mathematical details, see Appendix.

3.2. Feng model

An alternative approach of the centralized AEP is proposed by Feng et al. (2015) (i.e., Feng model hereafter). The Feng model, based on Färe and Grosskopf (2004) and Zhou et al. (2008), proposes the weak disposability technology with VRS assumption.[1] To apply Feng model, the parameters of upper bound ΔB_r^+ and lower bound ΔB_r^- of Δb_r are predetermined. For the carbon emission abatement, based on the nonnegativity property, i.e., $B_r - \Delta b_r \ge 0$, the upper bound ΔB_r^+ is equal to B_r. In contrast, the lower bound ΔB_r^- can be calculated by the Feng's lower bound model with respect to each specific firm r. Note that Feng model treats all inputs as fixed inputs to suggest a conservative solution; that is, input factors are not adjustable in Feng model. For mathematical details, see Appendix.

4. Decentralized AEP in an imperfectly competitive market

Contrast to centralized models, this section introduces the MiCP approach to identify the Nash equilibrium with respect to the decentralized AEP plan under imperfectly competitive market. The proposed model distinguishes the characteristics of fixed input and variable input in the Färe's technology and considers CRS case and NIRS (non-increasing returns to scale) case, respectively (Färe et al., 1994; Zhou et al., 2008).[2]

In an imperfectly competitive market, to build a price function of the desirable output, consider an inverse demand function as $P^Y(\hat{Y}) := P^{Y_0} - \tau\hat{Y}$, where $P^Y(\bullet) \ge 0$, $\hat{Y} = (\sum_k y_k + \bar{Y})$, $\bar{Y}$ is a constant

[1] Note that the Färe's VRS weak disposability of outputs excludes the original points and the desirable outputs must also be infinitesimal if undesirable outputs are infinitesimal. In addition, the Färe's VRS weak disposability puts an adjusting variable not less than 1 on the right-hand-side of desirable output and undesirable output constraints, but it leads to a nonlinear formulation. To address this issue, Zhou et al. (2008) gives a linear formulation used in our study.

[2] Färe's CRS technology and NIRS technology formulate linear complementarity problems (LCP) and guarantee the solution quality solved by PATH algorithm (Ferris and Munson, 2000); however, the decision variables $(x_{ir}, y_r, \Delta b_r)\ \forall\, i \in I_v$ lead to Färe's VRS technology forming a non-linear complementarity problem (NLCP) in which the solution quality cannot be guaranteed and thus it's out of scope of the current study.

representing the least and fixed output levels generated by the plants without market power, P^{Y_0} is a positive intercept, and $\tau \geq 0$ indicates the price sensitive coefficient of the desirable output. Apparently, the revenue function $P^Y(\hat{Y})y_r$ is concave. For the undesirable output of the power market, set a legal limit (i.e. CAP) on the quantity of a certain type of emission (eg. CO_2) an economy can emit in a period, to control emissions. We limit the abatement of the undesirable quantity $\sum_{r\in K}\Delta b_r = C$. Let D be the minimal amount of electricity consumption for demand fulfillment by these plants with market power, i.e. $\sum_{r\in K} y_r \geq D$, which also represents the lower bound of demand fulfilment in the inverse demand function $P^Y(\hat{Y})$. Without loss of generality, for the variable input of the power market, i.e., coal consumption or operating hours, we assume a competitive input market and the price of input is a constant, P_i^X, $\forall\, i \in I_v$.

4.1. Nash CRS model

We propose the MiCP under the Färe's CRS technology to identify the Nash solution (i.e., Nash CRS model hereafter). Similarly, as Feng's model, the parameters of upper bound ΔB_r^+ and lower bound ΔB_r^- of Δb_r should be predetermined first. Let x_{ir} and y_r be the decision variables of variable input i and output. The upper bound ΔB_r^+ is equal to B_r and the lower bound $\Delta B_r^- = B_r - \sum_{k\in K}\lambda_{kr}^* B_k$ can be calculated with the optimal solution λ_{kr}^* obtained by the following model (4).

The lower bound ΔB_r^- of CRS model:

$$\begin{aligned}
&\text{Max } \textstyle\sum_{k\in K} \lambda_{kr} B_k\\
&\text{s.t } \textstyle\sum_{k\in K} \lambda_{kr} X_{ik} \leq X_{ir},\ \forall\, i\in I_f;\\
&\textstyle\sum_{k\in K} \lambda_{kr} X_{ik} \leq x_{ir},\ \forall\, i\in I_v;\\
&\textstyle\sum_{k\in K} \lambda_{kr} Y_k \geq y_r;\\
&\lambda_{kr},\, x_{ir},\, y_r \geq 0,\ \forall\, k\in K,\, i\in I_v
\end{aligned} \tag{4}$$

Now, we consider each plant r would like to maximization its profit function. Given the parameters ΔB_r^- and ΔB_r^+ obtained from CRS model (4), and ε be a small positive number as the price of undesirable emission. The proposed model (5) is formulated for profit maximization with respect to each plant r restricted by Färe's CRS technology.

The profit maximization of CRS model:

$$\begin{aligned}
&\text{Max } (P^{Y_0} - \tau\hat{Y})y_r - \textstyle\sum_{i\in I_v} P_i^X x_{ir} - \varepsilon(B_r - \Delta b_r)\\
&\text{s.t } \textstyle\sum_{k\in K} \lambda_{kr} X_{ik} \leq X_{ir},\ \forall\, i\in I_f;\\
&\textstyle\sum_{k\in K} \lambda_{kr} X_{ik} \leq x_{ir},\ \forall\, i\in I_v;\\
&\textstyle\sum_{k\in K} \lambda_{kr} Y_k \geq y_r;\\
&\textstyle\sum_{k\in K} \lambda_{kr} B_k = B_r - \Delta b_r;\\
&\textstyle\sum_{r\in K} y_r \geq D;\\
&\textstyle\sum_{r\in K} \Delta b_r = C;\\
&\Delta b_r \text{ unrestricted and } \Delta b_r \in [\Delta B_r^-, \Delta B_r^+];\\
&x_{ir},\, y_r,\, \lambda_{kr} \geq 0,\ \forall\, k\in K,\quad i\in I_v
\end{aligned} \tag{5}$$

where the objective function includes three terms: maximizing revenue, minimizing the cost of variable input, minimizing the cost of emission. In particular, the term $\varepsilon(B_r - \Delta b_r)$ is used for reducing multiple solution issue (generated by MiCP model (7) later) and it is close to zero implies that a plant's productive behavior depends on physical profit maximization and the regulation of pollutant emission is only a constraint rather than an objective function. This assumption conforms with business practice of power plant in an imperfectly competitive market.

To solve for a Nash equilibrium associated with model (5), define the Lagrangian function as:

$$\begin{aligned}
L_r(x_{ir}, y_r, \Delta b_r, \lambda_{kr}, \varphi 1_{ir}, \varphi 2_{ir}, \varphi 3_r, \varphi 4_r, \varphi 5, \varphi 6, \varphi 7_r, \varphi 8_r) := &\left(P^{Y_0} - \tau\hat{Y}\right)y_r - \textstyle\sum_{i\in I_v} P_i^X x_{ir} - \varepsilon(B_r - \Delta b_r) - \displaystyle\sum_{i\in I_f}\varphi 1_{ir}\left(\textstyle\sum_{k\in K}\lambda_{kr}X_{ik} - X_{ir}\right)\\
&- \sum_{i\in I_v}\varphi 2_{ir}\left(\textstyle\sum_{k\in K}\lambda_{kr}X_{ik} - x_{ir}\right) - \varphi 3_r\left(y_r - \textstyle\sum_{k\in K}\lambda_{kr}Y_k\right) - \varphi 4_r\left(\textstyle\sum_{k\in K}\lambda_{kr}B_k - B_r + \Delta b_r\right)\\
&- \varphi 5\left(D - \textstyle\sum_{r\in K} y_r\right) - \varphi 6\left(C - \textstyle\sum_{r\in K}\Delta b_r\right) - \varphi 7_r(\Delta B_r^- - \Delta b_r) - \varphi 8_r(\Delta b_r - \Delta B_r^+),
\end{aligned} \tag{6}$$

where $\varphi 1_{ir}$, $\varphi 2_{ir}$, $\varphi 3_r$, $\varphi 4_r$, $\varphi 5$, $\varphi 6$, $\varphi 7_r$ and $\varphi 8_r$ are the Lagrange multipliers corresponding to each constraint (except nonnegativity constraint) in model (5).

Then, using the first-order conditions, the MiCP is formulated as:

$$\begin{aligned}
&0 \leq x_{ir} \perp -P_i^X + \varphi 2_{ir} \leq 0, \quad \forall\, i\in I_v,\, r\in K\\
&0 \leq y_r \perp P^{Y_0} - \tau\hat{Y} - \tau y_r - \varphi 3_r + \varphi 5 \leq 0, \quad \forall\, r\in K\\
&\varepsilon - \varphi 4_r + \varphi 6 + \varphi 7_r - \varphi 8_r = 0 (\Delta b_r \text{ unrestricted}), \quad \forall\, r\in K\\
&0 \leq \lambda_{kr} \perp - \textstyle\sum_{i\in I_f}\varphi 1_{ir}X_{ik} - \sum_{i\in I_v}\varphi 2_{ir}X_{ik} + \varphi 3_r Y_k - \varphi 4_r B_k \leq 0,\\
&\forall\, k, r\in K\\
&0 \leq \varphi 1_{ir} \perp \textstyle\sum_{k\in K}\lambda_{kr}X_{ik} - X_{ir} \leq 0, \quad \forall\, i\in I_f,\, r\in K\\
&0 \leq \varphi 2_{ir} \perp \textstyle\sum_{k\in K}\lambda_{kr}X_{ik} - x_{ir} \leq 0, \quad \forall\, i\in I_v,\, r\in K\\
&0 \leq \varphi 3_r \perp y_r - \textstyle\sum_{k\in K}\lambda_{kr}Y_k \leq 0, \quad \forall\, r\in K\\
&\textstyle\sum_{k\in K}\lambda_{kr}B_k - B_r + \Delta b_r = 0 (\varphi 4_r \text{ unrestricted}), \quad \forall\, r\in K\\
&0 \leq \varphi 5 \perp D - \textstyle\sum_{r\in K} y_r \leq 0\\
&C - \textstyle\sum_{r\in K}\Delta b_r = 0\, (\varphi 6 \text{ unrestricted}),\\
&0 \leq \varphi 7_r \perp \Delta B_r^- - \Delta b_r \leq 0, \quad \forall\, r\in K\\
&0 \leq \varphi 8_r \perp \Delta b_r - \Delta B_r^+ \leq 0, \quad \forall\, r\in K
\end{aligned} \tag{7}$$

In literature, for the PPS estimated by the DEA frontier with input and desirable output case, the Nash solution exists by solving MiCP if the profit function is concave and PPS is a convex set (Lee and Johnson, 2015; Lee, 2016). This study extends to the undesirable output case as model (5). In model (5), the objective function $(P^{Y_0} - \tau\hat{Y})y_r - \sum_{i\in I_v} P_i^X x_{ir} - \varepsilon(B_r - \Delta b_r)$ is concave on a convex PPS $(x_{ir}, y_r, b_r) \in \tilde{T}$, and it verifies the existence of the Nash equilibrium solution generated from the proposed MiCP, i.e., model (7). We derive Theorem 4.1.

Theorem 4.1. *The proposed MiCP* (7) *generates unique Nash equilibrium solution* $(x_{ir}, y_r, B_r - \Delta b_r) \in \tilde{T}$, *where* $\tilde{T}$ *is Färe's convex CRS technology, and satisfies the demand fulfillment constraint* $\sum_{r\in K} y_r \geq D$ *and the cap constraint* $\sum_{r\in K}\Delta b_r = C$.

Proof: See Appendix.

Note that if we investigate the dimensions of desirable output versus undesirable output, Färe's weak disposability technology may reveal some flaws in efficiency estimation; that is, some inefficient firm projected to the misspecified efficient frontier (i.e. increasing bad output but reducing good output) (Kuosmanen, 2005; Kuosmanen and Podinovski, 2009; Chen and Delmas, 2012). However, this study applies Färe's technology since it is helpful to give a comparison to literature (eg. Lozano model and Feng model), and, in fact, the Nash equilibrium generated by the proposed MiCP is justified and won't be on the misspecified efficient frontier due to profit maximization of model (5) implying allocatively efficient (see Appendix for details). In addition, the Nash solution does not locate on the hyperplane representing the

free disposability of desirable output that shows dual variables equal to zero on the desirable output constraints. These restrictions on the Färe's technology imply an upper bound of adjusted undesirable output level. Furthermore, the "CAP" constraint of the undesirable output also implicitly restricts the Färe's technology.

4.2. Nash NIRS model

For NIRS technology, similarly, the upper bound ΔB_r^+ is equal to B_r and the lower bound $\Delta B_r^- = B_r - \sum_{k\in K} \lambda_{kr}^* B_k$ can be calculated by the following NIRS model (8).

The lower bound ΔB_r^- of NIRS model:

$$\begin{aligned}
&\text{Max } \textstyle\sum_{k\in K} \lambda_{kr} B_k \\
&\text{s.t } \textstyle\sum_{k\in K} \lambda_{kr} X_{ik} \le X_{ir}, \quad \forall\ i \in I_f; \\
&\textstyle\sum_{k\in K} \lambda_{kr} X_{ik} \le x_{ir}, \quad \forall\ i \in I_v; \\
&\textstyle\sum_{k\in K} \lambda_{kr} Y_k \ge y_r; \\
&\textstyle\sum_{k\in K} \lambda_{kr} \le 1 \\
&\lambda_{kr}, x_{ir}, y_r \ge 0, \forall\ k \in K, i \in I_v
\end{aligned} \tag{8}$$

For NIRS technology, add new constraint $\sum_{k\in K} \lambda_{kr} \le 1$ in model (5). Let $\varphi 9_r$ be the Lagrange multiplier regarding the constraint $\sum_{k\in K} \lambda_{kr} \le 1$ and thus we add the new term $-\varphi 9_r(\sum_{k\in K} \lambda_{kr} - 1)$ into Lagrangian function as equation (6).

Then, using the first-order conditions, the MiCP (7) is corrected by replaced (9.1) and added (9.2) to form the MiCP.

$$0 \le \lambda_{kr} \perp -\sum_{i\in I_f} \varphi 1_{ir} X_{ik} - \sum_{i\in I_v} \varphi 2_{ir} X_{ik} + \varphi 3_r Y_k - \varphi 4_r B_k - \varphi 9_r \le 0,\ \forall\ k,\ r \in K \tag{9.1}$$

$$0 \le \varphi 9_r \perp \textstyle\sum_{k\in K} \lambda_{kr} - 1 \le 0, \quad \forall\ r \in K \tag{9.2}$$

We can directly derive the existence property of Nash equilibrium in Nash NIRS model from Theorem 4.1.

5. Empirical study

We conduct an empirical study to solve different AEP models in plant-level coal-fired power plants operating in China in 2013.[3] We focus on the North and the Northeast regions. Zhao et al. (2014) shows the CO_2 emission intensity (unit: tonne over gross domestic product (GDP)) in these two regions from 1991 to 2010; in particular, Shanxi presents top 1 among all provinces. They claim that coal consumption accounted for the highest rate of total energy consumption in China, and the power transfer efficiency of coal is relatively lower than other energy usage (eg. petroleum, natural gas and hydro-power). They conclude that the higher the ratio of coal consumption the higher the CO_2 emission intensity in each province. In addition, according to the Natural Resources Defense Council, in China 60% of PM2.5 (airborne particles with a diameter of less than 2.5 μm) is directly generated from coal burning and is especially high in the two regions (Yang, 2014). Thus, these two regions show significant abatement potential for emissions reduction and a greater influence on the national goal (Wei et al., 2012). In our study, the North region includes Beijing, Tianjin, Hebei, Shanxi, Shandong, and Inner Mongolia, and the Northeast region includes Liaoning, Jilin, and Heilongjiang.

For numerical illustration, we assume a regulated and imperfectly competitive power market in the North and the Northeast regions, and use the centralized AEP models and the proposed decentralized AEP models to suggest AEP, respectively.[4] We assume input markets are perfectly competitive with exogenous price and consider the imperfectly competitive electricity market for profit maximization. We investigate 33 coal-burning power plants with the nameplate capacity larger than 1 million kW, which has larger market power to affect the market price. Section 5.1 describes the dataset, Section 5.2 describes the empirical results of different AEP models, and Section 5.3 provides efficiency analysis before and after AEP to validate the proposed Nash AEP models. Section 5.4 provides the managerial implications and policy recommendations based on the AEP results.

5.1. Dataset

The balanced plant-level data set comprises 33 coal-burning power plants operating in 2013.[5] We consider nameplate capacity as the fixed input, coal consumption and average operating hours as two variable inputs, the annual amount of coal-fired electricity generation as a single desirable output, and the annual amount of CO_2 emission as a single undesirable output.[6] The data is collected from the China Electric Power Yearbook (CEPP, 2014). In particular, the plant-level pollutant emissions are estimated by a plant's proportion of coal consumption multiplied by a province's total emissions and average emission factor (IPCC, 2013; EEA, 2013). The total CO_2 emission of the two regions is assigned to one single cap, which implies the AEP will be generated under this restriction. This study assumes 1% emission reduction; that is, C= $0.01 \times \sum_{k\in K} B_k = \sum_{r\in K} \Delta b_r$. Table 1 lists the summary statistics.

Assume a linear price function, i.e., inverse demand function, $P^Y(\hat{Y}) := 4.5 \times 10^7 - 123\hat{Y}$ (unit: CNY$ per 10^8 kWh) based on China's average on-grid electricity price of coal-fired power CNY$427.01 per MWh and total electricity generation 15,103 (10^8 kWh) in the two regions in 2013.[7] Note that $\hat{Y} = \sum_k y_k + 10{,}975$ and the constant 10,975 represent the electricity generated only by coal-fired plants with a nameplate capacity less than 1 M kW. The price of coal is CNY$590 per tonne, and the price of average operating hours is a relative small constant.[8] The next section explains the results of the centralized AEP models and the decentralized Nash AEP models.

5.2. Allocation of emission permit (AEP)

The study applies five models for AEP estimation. They are Egalitarianism model, Lozano model with CRS technology, Feng model with VRS technology, Nash model with CRS technology, and Nash model with NIRS technology. In particular, Egalitarianism is based on the population size and we estimate the population of each plants by

[3] An empirical study of China's coal-fired power market in 2016 was described in Appendix. It provides similar results as 2013 case.

[4] These regions generate more electricity and pollutants, and have larger nameplate capacity with market power which could directly (or indirectly) affect the market clearing price. In addition, the proposed inverse demand function is more generalized since we can also consider a typical exogenous price by setting the parameter τ close or equal to zero in the inverse demand function.

(footnote continued)

[5] We exclude Beijing and Jilin because they have no coal-fired power plants with nameplate capacity larger than 1 M kW.

[6] Due to the difficulties in plant-level data collection, this study suggests nameplate capacity and average operating hours of power generation for an approximation of capital stock or labor stock. However, this could be improved for future work. In addition, we assume the homogenous quality of coal used in the North and the Northeast regions.

[7] We assume a linear price function and estimate it by a simple linear regression with a few data points of total electricity generation and electricity price in 2012 and 2013. Thus, the price function should be validated in the further research. In fact, the price function with the endogeneity assumption provides 1) a more generalized model (i.e. it can represent the exogenous case if the slope coefficient equal to zero); 2) a scenario analysis for an imperfectly competitive energy market or the deregulation of electricity market when market structure changes.

[8] We assume a small constant of the price of average operating hours depending on nameplate capacity since negative profit could happen if a larger cost side in profit function.

Table 1
Statistics for 33 coal-burning power plants operating in North and Northeast regions of China in 2013.

Statistics	Nameplate Capacity (10^4 kW)	Coal (10^4 tonne)	Average Operating Hours	Electricity (10^8 kWh)	CO_2 (10^3 tonne)
Avg.	232.8	687.6	5078.4	125.1	14,477.2
Std. Dev.	72.4	287.2	905.2	59.5	8,285.2
Max	480	1,767.6	6761	385	46,751.1
Min	160	315.9	3116	62	6,945.9

the proportion of the electricity generated in the province. Table 2 and Fig. 1 give AEP results.

In Table 2 and Fig. 1, the plants located in Hebei, Shanxi, and Tianjin present the negative AEP (i.e. these plans should allow to produce more emission) except Egalitarianism model while the plants in Inner Mongolia with the positive values in five AEP models (both centralized and decentralized models) indicate urgent emission reduction in this area. The inconsistent AEP decisions occur between centralized models and decentralized models and are presented in Shandong, Liaoning, and Heilongjiang. For example, the Lozano model claim AEP with negative values in Shandong but positive values suggested by Nash model. The results provide the insight implying that a totally different decision could happen between different market assumptions; that is, the centralized models without considering price information contrast to the Nash equilibrium considering endogenous price in an imperfect competition.

In summary, Egalitarianism model gives positive reduction of all plants with the lower variation (i.e. standard deviation) while Nash CRS and Nash NIRS provides significant reallocation of AEP among plants (i.e. larger variation). Table 3 shows another way to compare the five AEP models by using the correlation coefficients and Wilcoxon matched-pairs signed-rank test. The results from using Egalitarianism, Lozano CRS, and Feng VRS are highly-correlated (no matter positive or negative correlation) since they use centralized model without price information while Nash CRS and Nash NIRS models are similar due to decentralized model with endogenous price. The result strongly supports developing the decentralized AEP model to fill the gap in literature. In addition, Wilcoxon test showing no one with p-value smaller than 0.05 in any pair comparison indicates that the medians of AEP in five model are not dissimilar. Ward's method (Ward, 1963) also shows the hierarchical clustering result of the five AEP models and forms two main clusters-centralized models and decentralized models.

5.3. Efficiency analysis before and after AEP

To validate the AEP of five models, this section provides an efficiency analysis before and after the reallocation of emission permits by using undesirable-output-oriented model (3). The results are shown as Table 4 and Fig. 2. The efficiency of each plant estimated before AEP is called “Origin”. As a whole, no matter before or after AEP plants in the province Hebei and Shanxi present better efficiency (above than average) while plants in Inner Mongolia present poor performance. Shandong2 and Liaoning4 are efficient in all efficiency measures (one measure in Sandong2 is 0.997 close to 1). In addition, Fig. 2 shows that

Table 2
AEP results of the five models.

AEP	Nameplate Capacity (10^4 kW)	Centralized Models			Decentralized Models	
Plant		Egalitarianism	Lozano CRS	Feng VRS	Nash CRS	Nash NIRS
Hebei1	256	272.4	−490.9	−2807.0	−1923.1	−1923.1
Hebei2	252	266.8	−3955.6	−1166.6	370.2	370.2
Hebei3	252	265.0	−479.2	−5150.7	−2003.1	−2003.1
Hebei4	250	250.3	−453.1	−3754.8	−2596.8	−2596.8
Shanxi1	252	115.5	−549.6	−668.1	−2155.3	−2155.3
Shanxi2	240	97.3	−463.5	−751.6	−3468.0	−3468.0
Shanxi3	210	95.7	−456.9	−256.0	−1822.3	−1822.3
Shanxi4	180	72.0	−342.6	0.0	−2719.7	−2719.7
Shanxi5	180	71.2	−341.4	−58.1	−2748.6	−2748.6
Shanxi6	180	64.1	−305.8	−2204.9	−3588.8	−3588.8
Tianjin1	200	157.7	198.5	323.8	−301.4	−301.4
Shandong1	270	203.3	0.0	0.0	−3175.8	−4144.8
Shandong2	258	241.6	0.0	0.0	0.0	0.0
Shandong3	204	165.0	−5410.2	89.4	2208.6	2208.6
Shandong4	200	142.6	−2076.1	−55.8	573.2	573.2
Shandong5	200	169.0	−4587.0	0.0	2882.5	2882.5
Shandong6	200	150.5	−4244.7	152.3	1172.0	1172.0
Shandong7	179	125.4	−1023.1	−382.6	282.5	282.5
Shandong8	173	108.3	0.0	−896.9	−865.2	−865.2
Shandong9	161	116.2	−775.0	0.0	−1555.1	1216.2
Inner Mongolia1	480	128.0	0.0	0.0	17926.6	21990.6
Inner Mongolia2	372	65.2	4148.4	2912.3	9793.5	7372.1
Inner Mongolia3	340	54.5	5342.7	3958.7	6462.4	2119.3
Inner Mongolia4	318	54.5	5501.1	4578.8	7767.9	2922.8
Inner Mongolia5	240	48.6	381.2	5911.0	9344.5	9344.5
Inner Mongolia6	180	21.6	3200.8	1792.7	−157.0	−157.0
Liaoning1	360	261.2	2754.1	1631.5	−4254.9	−7397.0
Liaoning2	240	167.9	1767.5	1206.6	−3269.1	−3269.1
Liaoning3	184	123.8	1307.7	373.4	−2804.7	−2804.7
Liaoning4	160	105.2	1101.7	0.0	−5719.1	−2662.3
Heilongjiang1	190	213.0	1585.2	0.0	−2719.2	−2719.2
Heilongjiang2	161	189.0	1696.3	0.0	−3140.0	−368.6
Heilongjiang3	160	195.0	1746.7	0.0	−3019.2	37.7
# of reduction (positive value)		33	13	11	11	13
Std. Dev.	72.4	71.5	2458.7	2087.0	4900.5	4992.1
Max	480	272.4	5501.1	5911.0	17926.6	21990.6
Min	160	21.6	−5410.2	−5150.7	−5719.1	−7397.0

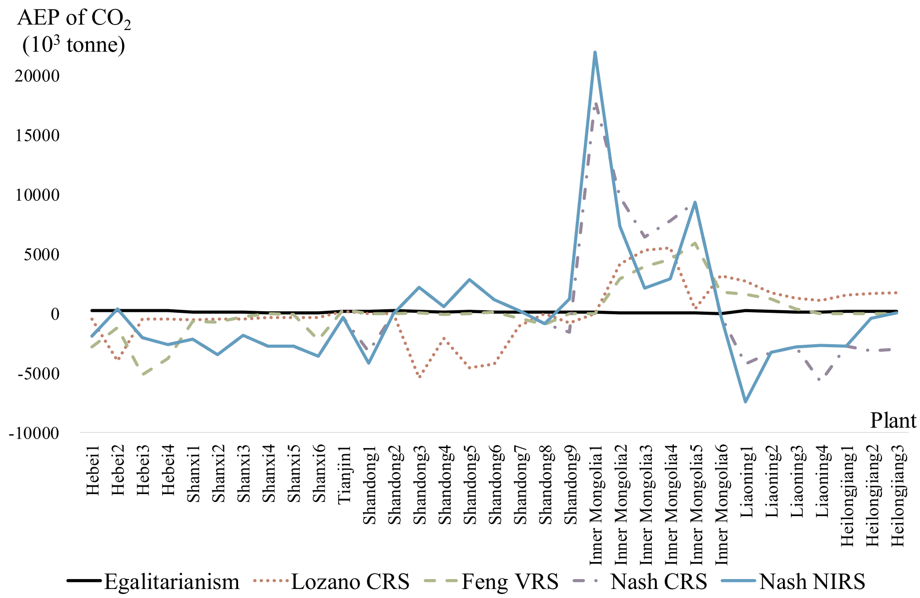

Fig. 1. AEP results of the five models.

Table 3
Correlation coefficients and Wilcoxon matched-pairs signed-rank test of AEP in the five models.

Correlation Coefficient and Wilcoxon Test	Lozano CRS	Feng VRS	Nash CRS	Nash NIRS
Egalitarianism	−0.326 (0.851)	−0.569[a] (0.241)	−0.321 (0.136)	−0.264 (0.118)
Lozano CRS		0.496[a] (0.382)	0.140 (0.501)	−0.004 (0.369)
Feng VRS			0.505[a] (0.454)	0.346[a] (0.369)
Nash CRS				0.932[a] (0.878)

(·): P-value of Wilcoxon matched-pairs signed-rank test.
[a] Pass significant testing at level 0.05.

two Nash models can significantly increase the average efficiency after AEP; in particular, in Shandong, Inner Mongolia, and Heilongjiang, but two models drop efficiency slightly in Hebei and Shanxi. Note that in Fig. 2 we only draw the Egalitarianism to represent the Origin due to they are very similar with correlation coefficient close to 1 in Table 5.

For the model comparison, before the AEP, the average efficiency and standard deviation of the 33 plants are 0.812 and 0.155. While, after the AEP, egalitarianism model, Lozano CRS and Feng VRS provide the similar and average efficiencies (0.812, 0.805, and 0.809 respectively) and present the poor performance than that before AEP. For the decentralized models, Nash CRS and Nash NIRS provide better average efficiency scores (0.896 and 0.860 respectively) and showing the smaller standard deviation (0.111 and 0.139) indicates that decentralized AEP benefits reducing the difference among plants and every plants get closer since they approach the Nash equilibrium solution. In particular, after AEP Nash CRS leads to 11 efficient plants. The results also validate the contribution and the development of the decentralized AEP models. Note that the result does not mean reducing the discrimination power of efficiency estimation but showing the gap reduction among plants after Nash AEP.

In addition, Table 5 shows the correlation coefficients and Wilcoxon tests of efficiency scores in the five models. The results show that all measures present high correlations (larger than 0.5) no matter before AEP or after AEP except the lower correlation between Lozano CRS and two proposed Nash models. In particular, the efficiency before AEP (i.e. origin) is totally similar to that after AEP by Egalitarianism model. This means that though Egalitarianism model is more intuitive and simple, its AEP only based on the population shows nothing contributing to the efficiency due to too small variability of AEP (standard deviation is 71.5 in Table 2) changing nothing.

Thus, this section concludes that the contribution of efficiency by the centralized models is limited due to relatively smaller variability of AEP (see standard deviation in Table 2); while the proposed decentralized models claim plants may adjust the desirable-output level to partially affect the market and the "invisible hand" (interpreted by Nash equilibrium) makes AEP more efficient in an imperfectly competitive power market. In particular, without considering the price and market structure, the centralized models described in this study underestimate the possibility for potential improvement by AEP. That is, AEP is not only an optimization method for reallocation but also brings an opportunity for improving market efficiency indeed.[9]

5.4. Managerial implications

The AEP and efficiency results presented above show that an essential advantage to develop an alternative AEP model (i.e. decentralized) for achieving the goals of emission regulation and economic development simultaneously. First, as shown in Table 2, the centralized model and the decentralized model can provide different managerial implications of AEP. If policy maker would like to introduce the AEP into some regional market in the very beginning, the centralized model with small standard deviation of AEP results is suggested to alleviate

[9] The reason why the endogenous price can affect the AEP decision is that all plants' input-and-output decisions affect each other since price is affected by the total output in the market. In fact, Lee and Johnson (2015) claimed "rational inefficiency" which firms intend to maintain a lower output level away from the efficient frontier for avoiding a significant price drop in the market. Similarly, the AEP decision can be affected in an imperfectly competitive power market due to the changes of the plants' production behavior.

Table 4
Efficiency analysis before and after AEP.

Efficiency	Before AEP	After AEP				
Plant	Origin	Egalitarianism	Lozano CRS	Feng VRS	Nash CRS	Nash NIRS
Hebei1	0.934	0.938	0.901	0.668	0.855	0.853
Hebei2	0.793	0.795	0.632	0.738	0.818	0.798
Hebei3	0.932	0.937	0.900	0.669	0.855	0.853
Hebei4	0.932	0.937	0.901	0.748	0.837	0.836
Shanxi1	0.956	0.950	0.918	0.909	0.870	0.868
Shanxi2	0.962	0.956	0.925	0.836	0.841	0.841
Shanxi3	0.970	0.967	0.936	0.948	0.955	0.954
Shanxi4	1.000	1.000	0.972	1.000	1.000	1.000
Shanxi5	0.993	0.993	0.965	0.987	0.993	0.991
Shanxi6	1.000	1.000	0.973	0.817	1.000	0.959
Tianjin1	0.886	0.888	0.908	0.911	1.000	0.988
Shandong1	1.000	1.000	1.000	1.000	0.872	0.822
Shandong2	1.000	1.000	1.000	1.000	1.000	0.997
Shandong3	0.751	0.751	0.550	0.751	0.958	0.933
Shandong4	0.748	0.748	0.647	0.749	0.886	0.861
Shandong5	0.749	0.749	0.577	0.749	1.000	0.987
Shandong6	0.754	0.754	0.574	0.754	0.923	0.890
Shandong7	0.772	0.774	0.711	0.778	1.000	0.928
Shandong8	0.819	0.819	0.786	0.836	0.997	0.903
Shandong9	0.892	0.889	0.531	0.892	1.000	1.000
Inner Mongolia1	0.697	0.688	0.697	0.697	1.000	1.000
Inner Mongolia2	0.516	0.509	0.722	0.568	0.692	0.570
Inner Mongolia3	0.517	0.510	0.738	0.606	0.654	0.512
Inner Mongolia4	0.517	0.510	0.551	0.623	0.699	0.530
Inner Mongolia5	0.524	0.517	0.533	0.697	0.880	0.841
Inner Mongolia6	0.549	0.545	0.789	0.678	0.816	0.775
Liaoning1	0.751	0.750	0.892	0.829	0.619	0.539
Liaoning2	0.772	0.775	0.924	0.873	0.760	0.760
Liaoning3	0.848	0.852	0.961	0.928	1.000	0.897
Liaoning4	1.000	1.000	1.000	1.000	1.000	1.000
Heilongjiang1	0.766	0.777	0.909	0.873	0.908	0.830
Heilongjiang2	0.748	0.752	0.778	0.839	0.886	0.880
Heilongjiang3	0.755	0.759	0.777	0.755	1.000	1.000
Elec. generation (10^8 kWh)	4128	4128	4919.8	4517.1	5477.8	5334
# of efficient plants	5	5	3	4	11	5
Avg.	0.812	0.812	0.805	0.809	0.896	0.860
Std. Dev.	0.155	0.157	0.156	0.122	0.111	0.139

the disagreement by considering the plants' resistance in implementation; while the decentralized model with large standard deviation of AEP results is more aggressive and encouraged due to a better performance shown in Table 4. In fact, in some cases, the economic performance is not the primary objective when the peer-induced fairness concern among plants needs to be considered (Ji et al., 2017a). AEP concentration to one plant or a few specific plants could lead to unfairness of these plants. The centralized model is suggested and

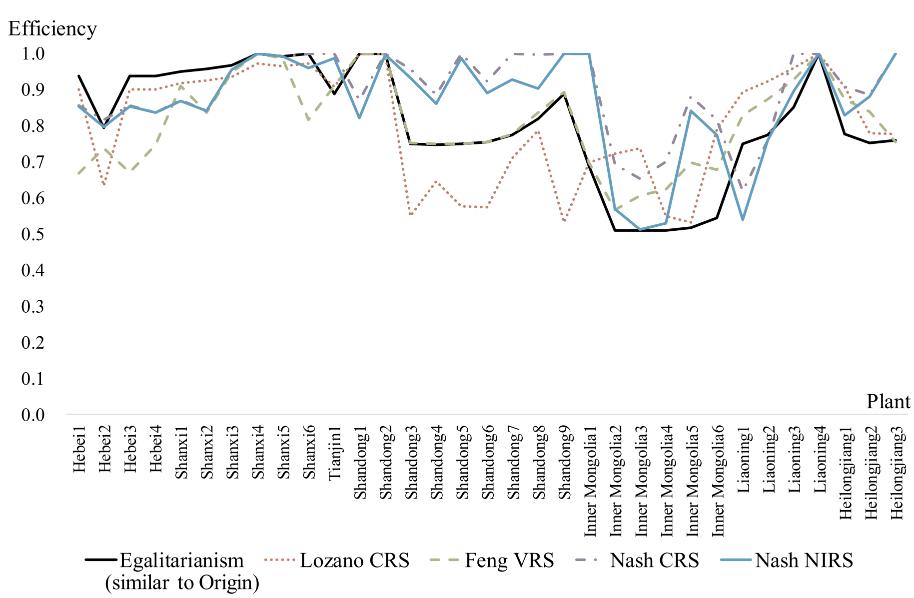

Fig. 2. Efficiency analysis of the five AEP models.

Table 5
Correlation coefficients and Wilcoxon matched-pairs signed-rank test of efficiency measures in the five models.

	Egalitarianism	Lozano CRS	Feng VRS	Nash CRS	Nash NIRS
Origin (Before AEP)	0.9997[a] (0.495)	0.682[a] (0.469)	0.757[a] (0.689)	0.526[a] (0.001[a])	0.620[a] (0.060)
Egalitarianism		0.684[a] (0.465)	0.756[a] (0.496)	0.528[a] (0.001[a])	0.620[a] (0.052)
Lozano CRS			0.615[a] (0.922)	0.110 (0.030[a])	0.166 (0.239)
Feng VRS				0.526[a] (0.0004[a])	0.553[a] (0.018[a])
Nash CRS					0.959[a] (0.000006[a])

(·): Wilcoxon matched-pairs signed-rank test.
[a] Pass significant testing at level 0.05.

restricts potential trading among plants when input resource (eg. coal) is insufficient or the quota of AEP is limited; in this case, the fairness receives much concern. While the decentralized model implying a better resource (eg. AEP, inputs, outputs, etc.) reallocation is encouraged to promote the market efficiency when government subsidies or allowance is available and capacity expansion of plants is required. Hence, two AEP models complement each other, and the policy maker should build the discipline to ensure a better tradeoff between fairness and market efficiency based on the market condition.

Second, comparing with the original plan in Table 4, we can obtain a 32.7% increase in power generation and a 10.3% increase in its productive efficiency aspect after applying the Nash CRS allocation scheme. The decentralized AEP model can lead to the better economic performance. In fact, the decentralized models restrict the dirty plants producing less (both electricity and CO2) and encourage the clean plants producing more from a profit-maximization aspect. However, this ideal situation is generally difficult to exercise due to the organizational resistance mentioned above. If the policy maker wants to maintain a high level of economic performance during the emission regulation, then he should focus on the potential trading of emission permits between these efficient plants and inefficient plants. In particular, the policy maker should strengthen the bargaining power of the efficient plants and ensure an effective AEP trading (or reallocation) among these plants.

Third, the policy maker is suggested to use the centralized model in the short run but to use the decentralized model in the long run. As mentioned above, the fairness is concerned and the centralized model providing a smaller difference of AEP among plants benefits the regulation development in the short run. The decentralized model has the possibility of allocating most of permits to one specific plant (i.e. Inner Mongolia1), causing excessive resource concentration in the short run. This situation could practically weaken economic performance; particularly for a larger plant, which may be required to build a costly and huge transmission network across regions in China and the loss of electricity through distant transportation is significant. However, in the long run, the market efficiency and productive efficiency are concerned and the "invisible hand" makes AEP more efficient through the decentralized AEP model. For a larger plant (i.e. Inner Mongolia1), to drive its productivity (technical efficiency from 0.697 to 1.000) will bring significant benefits (i.e. electricity generation and emission reduction) to the whole power market and enhance the market efficiency. Thus, policy maker can design the environmental regulation and divide it into several phases. We think the next power market phase will be a correction, and a step-by-step adjustment of AEP from short-run to long-run is a guideline for fairness and efficiency.

In real settings, a two-stage regulatory scheme is evident in many fields and industries of China's regional environmental management plans, such as "*Inner Mongolia main pollutant emission allowance verification plan*". The first stage sets the standard emission amount of pollution such as such as in the *Emission Standard of Air Pollutants for Coal-fired Power Plants*, and the second stage makes decision of AEP related to the total number of extra permit quotas to be allocated (Ji et al., 2017a). The centralized and decentralized AEP models are sufficiently tractable based on DEA formulation, and applicable to the two-stage regulatory scheme. In particular, both of them provide different insights to the practical environmental management. On one hand, the policy maker can simulate the efficiency analysis of before-and-after AEP before real allocation, and generate several simulation scenarios to maintain the fairness through the two-stage regulatory scheme. On the other hand, the policy maker should decide the AEP among plants more carefully because increasing the productive efficiency (eg. allocate permits to a few efficient plants or a larger plant) is a trade-off reducing the fairness of AEP.

6. Conclusion

This study proposes a decentralized AEP model and formulates the MiCP to identify the Nash equilibrium as an allocatively efficient benchmark in an imperfectly competitive power market. We describe five models for AEP estimation— Egalitarianism model, Lozano model with CRS technology, Feng model with VRS technology, Nash model with CRS technology, and Nash model with NIRS technology. An empirical study of coal-fired power plants operating in China in 2013 is conducted and the results show that the decentralized model complements the centralized model. That is, the AEP decision could be significantly different when considering the price and market structure. In the case study, the decentralized models provide better average efficiency scores after AEP and thus benefit reducing the difference among plants. The results validate the contribution and the development of the decentralized AEP models, and the study support the practical difficulties of implementing AEP in the different regulatory settings.

Knowing the AEP provides useful environmental policy guidelines, such as the allowance price in emissions trading markets and the penalty rates for emissions. In practice, the reallocation of emission permits is likely to meet with resistance from negatively affected plants and may also lead to an increase in monitoring costs to guarantee the reliability of the plant. In fact, setting a more stringent standard to control these emissions should improve China's carbon market. In 2013, China's State Council issued its Air Pollution Prevention and Control Action Plan to control coal consumption and set the target of coal consumption at less than 65% of total energy sectors in 2017. China's recent coal over-supply and electricity over-surplus in the coal-fired power plant sector provides a chance to restructure the emission trading system (ETS) and energy sectors in favor of renewable energy (Brown and Daigle, 2017).

We suggest that the development of decentralized AEP models to the latest data after the implementation of the pollution standards will provide useful data to support regulatory policy. In addition, DEA game cross-efficiency approach (Liang et al., 2008) provides the robust efficiency scores which can be investigated to support the AEP. Future research should investigate some uncertain issues, such as the volatility of electricity demand and price, and consider the social welfare maximization from government's aspect. In addition, it deserves the attention that factors used to promote the future cap-and-trade market in China mainland should be investigated and interpreted since the national market has not been activated now.

Acknowledgment

This research is funded by the Ministry of Science and Technology, Taiwan (MOST106-2628-E-006-009-MY3), Taiwan.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2019.03.114.

References

Aparicio, J., Landete, M., Monge, J.F., Sirvent, I., 2008. A new pricing scheme based on DEA for iterative multi-unit combinatorial auctions. Top 16, 319–344.
Banker, R., 1980. A game theoretic approach to measuring efficiency. Eur. J. Oper. Res. 5, 262–268.
Banker, R., Charnes, A., Cooper, W.W., Clarke, R., 1989. Constrained game formulations and interpretations for data envelopment analysis. Eur. J. Oper. Res. 40, 299–308.
Berk, M.M., den Elzen, M.G.J., 2001. Options for differentiation of future commitments in climate policy: how to realize timely participation to meet stringent climate goals? Clim. Policy 1 (4), 465–480.
Brown, M., Daigle, K., 2017. Coal on the Rise in China, U.S., India after Major 2016 Drop. http://www.chicagotribune.com/news/nationworld/ct-coal-china-india-us-20170626-story.html. Assessed Dec. 25, 2017.
CEPP (China Electric Power Press), 2014. China Electric Power Yearbook. China Electric Power Press in Chinese.
Chen, C.-M., Delmas, M., 2012. Measuring eco-inefficiency: a new frontier approach. Oper. Res. 60 (5), 1064–1079.
Chung, Y.H., Färe, R., Grosskopf, S., 1997. Productivity and undesirable outputs: a directional distance function approach. J. Environ. Manag. 51 (3), 229–240.
Dakpo, K.H., Jeanneaux, P., Latruffe, L., 2016. Modelling pollution-generating technologies in performance benchmarking: recent developments, limits and future prospects in the nonparametric framework. Eur. J. Oper. Res. 250 (2), 347–359.
den Elzen, M., Fekete, H., Höhne, N., Admiraal, A., Forsell, N., Hof, A.F., Olivier, J.G.J., Roelfsema, M., van Soest, H., 2016. Greenhouse gas emissions from current and enhanced policies of China until 2030: can emissions peak before 2030? Energy Policy 89, 224–236.
Deng, X., Yu, Y., Liu, Y., 2015. Temporal and spatial variations in provincial CO2 emissions in China from 2005 to 2015 and assessment of a reduction plan. Energies 8 (5), 4549–4571.
EEA (European Environment Agency), 2013. EMEP/EEA Air Pollutant Emission Inventory Guidebook 2013: Technical Guidance to Prepare National Emission Inventories. https://www.eea.europa.eu/publications/emep-eea-guidebook-2013 Dec. 25, 2017.
Färe, R., Grosskopf, S., 2004. Modeling undesirable factors in efficiency evaluation: comment. Eur. J. Oper. Res. 157, 242–245.
Färe, R., Grosskopf, S., Lovell, C.A.K., 1994. Production Frontiers. Cambridge University Press, Cambridge.
Färe, R., Grosskopf, S., Pasurkajr, C., 2007. Environmental production functions and environmental directional distance functions. Energy 32 (7), 1055–1066.
Feng, C., Chu, F., Ding, J., Bi, G., Liang, L., 2015. Carbon Emissions Abatement (CEA) allocation and compensation schemes based on DEA. Omega 53, 78–89.
Ferris, M.C., Munson, T.S., 2000. Complementarity problems in GAMS and the PATH solver. J. Econ. Dyn. Control 24, 165–188.
Gabriel, S.A., Conejo, A.J., Fuller, J.D., Hobbs, B.F., Ruiz, C., 2013. Complementarity Modeling in Energy Markets. Springer-Verlag, New York.
Gomes, E.G., Lins, M.P.E., 2008. Modeling undesirable outputs with zero sum gains data envelopment analysis models. J. Oper. Res. Soc. 59 (5), 616–623.
Hobbs, B.F., Pang, J.S., 2007. Nash-Cournot equilibria in electric power markets with piecewise linear demand functions and joint constraints. Oper. Res. 55 (1), 113–127.
IPCC (Intergovernmental Panel on Climate Change), 2013. Climate Change 2013: the Physical Science Basis. Working Group I Contribution to the Fifth Assessment Report of the IPCC. Cambridge University Press. https://www.ipcc.ch/report/ar5/index.shtml Assessed Dec. 25, 2017.
Ji, X., Li, G., Wang, Z., 2017a. Allocation of emission permits for China's power plants: a systemic Pareto optimal method. Appl. Energy 204, 607–619.
Ji, X., Sun, J., Wang, Y., Yuan, Q., 2017b. Allocation of emission permits in large data sets: a robust multi-criteria approach. J. Clean. Prod. 142, 894–906.
Johansen, L., 1968. Production functions and the concept of capacity. Recherches Recentes sur la Function de Production, Collection Economie et Mathematique et Econometrie 2, 46–72.
King, D., Richards, K., Tyldesley, S., 2011. Copenhagen and Cancun. International Climate Change Negotiations: Key Lessons and Next Steps. Smith School of Enterprise and the Environment, University of Oxford, Oxford, UK, pp. 11–16.
Kuosmanen, T., 2005. Weak disposability in nonparametric productivity analysis with undesirable outputs. Am. J. Agric. Econ. 87 (4), 1077–1082.
Kuosmanen, T., Podinovski, V.V., 2009. Weak disposability in nonparametric production analysis; reply to Färe and Grosskopf. Am. J. Agric. Econ. 91 (2), 539–545.
Lee, C.-Y., 2015. Distinguishing operational performance in power production: a new measure of effectiveness by DEA. IEEE Trans. Power Syst. 30 (6), 3160–3167.
Lee, C.-Y., 2016. Nash-profit efficiency: a measure of changes in market structures. Eur. J. Oper. Res. 255 (2), 659–663.
Lee, C.-Y., 2018. Mixed-strategy Nash equilibrium in data envelopment analysis. Eur. J. Oper. Res. 266 (3), 1013–1024.
Lee, C.-Y., Johnson, A.L., 2015. Measuring efficiency in imperfectly competitive markets: an example of rational inefficiency. J. Optim. Theory Appl. 164 (2), 702–722.
Lee, C.-Y., Wang, K., 2019. Nash marginal abatement cost estimation of air pollutant emissions using the stochastic semi-nonparametric frontier. Eur. J. Oper. Res. 273 (1), 390–400.
Lee, C.-Y., Zhou, P., 2015. Directional shadow price estimation of CO2, SO2 and NOx in the United States coal power industry 1990-2010. Energy Econ. 51, 493–502.
Lee, J.D., Park, J.B., Kim, T.Y., 2002. Estimation of the shadow prices of pollutants with production/environment inefficiency taken into account: a nonparametric directional distance function approach. J. Environ. Manag. 64, 365–375.
Liang, L., Wu, J., Cook, W.D., Zhu, J., 2008. The DEA game cross-efficiency model and its Nash equilibrium. Oper. Res. 56 (5), 1278–1288.
Liu, Z., 2015. China's Carbon Emissions Report 2015. Cambridge, Mass.: Report for Sustainability Science Program. Mossavar-Rahmani Center for Business and Government, Harvard Kennedy School, Energy Technology Innovation Policy research group, Belfer Center for Science and International Affairs, Harvard Kennedy School May 2015.
Lozano, S., 2013. DEA production games. Eur. J. Oper. Res. 231, 405–413.
Lozano, S., Villa, G., Brännlund, R., 2009. Centralised reallocation of emission permits using DEA. Eur. J. Oper. Res. 193 (3), 752–760.
Marshall, A., 1920. Principles of Economics, eighth ed. Macmillan and Co., Ltd, London.
Shephard, R.W., 1974. Indirect Production Functions. Meisenheim Am Glan: AntonHainVerlag Mathematical systems in economics, 10.
Stigler, G., 1939. Production and distribution in the short run. J. Political Econ. 47 (3), 305–327.
Sun, J., Wu, J., Liang, L., Zhong, R.Y., Huang, G.Q., 2014. Allocation of emission permits using DEA: centralised and individual points of view. Int. J. Prod. Res. 52 (2), 419–435.
Wang, K., Zhang, J., Wei, Y.-M., 2017. Operational and environmental performance in China's thermal power industry: taking an effectiveness measure as complement to an efficiency measure. J. Environ. Manag. 192 (1), 254–270.
Ward, J.H., 1963. Hierarchical grouping to optimize an objective function. J. Am. Stat. Assoc. 58 (301), 236–244.
Wei, C., Ni, J., Du, L., 2012. Regional allocation of carbon dioxide abatement in China. China Econ. Rev. 23, 552–565.
Wu, J., Liang, L., Yang, F., Yan, H., 2009. Bargaining game model in the evaluation of decision making. Expert Syst. Appl. 36, 4357–4362.
Yang, F., 2014. How the Coal Consumption Affects the Climate in China. Available at: http://www.nrdc.cn/coalcap/ June 14, 2016. (in Chinese).
Zhao, X., Burnett, J.W., Fletcher, J.J., 2014. Spatial analysis of China province-level CO2 emission intensity. Renew. Sustain. Energy Rev. 33, 1–10.
Zhou, P., Ang, B.W., Poh, K.L., 2008. Measuring environmental performance under different environmental DEA technologies. Energy Econ. 30 (1), 1–14.